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Compressor Engineering
Refrigeration and Air Conditioning
High Performance Buildings

FROM ENERGY SIGNATURE TO CLUSTER ANALYSIS: AN INTEGRATED APPROACH

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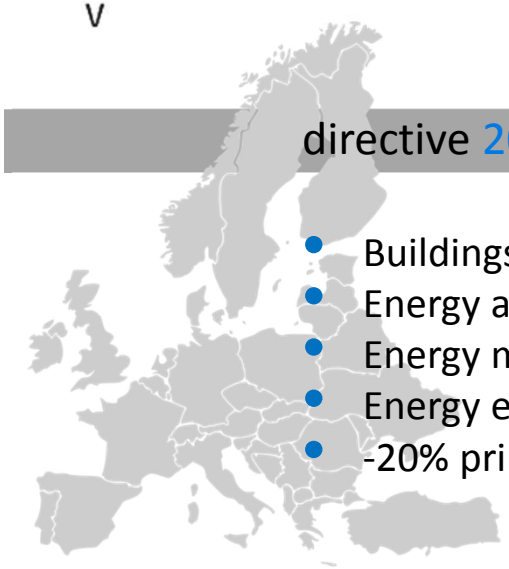
- Introduction
- Objective and case study
- Method
- Results
- Conclusions
- Future outlooks



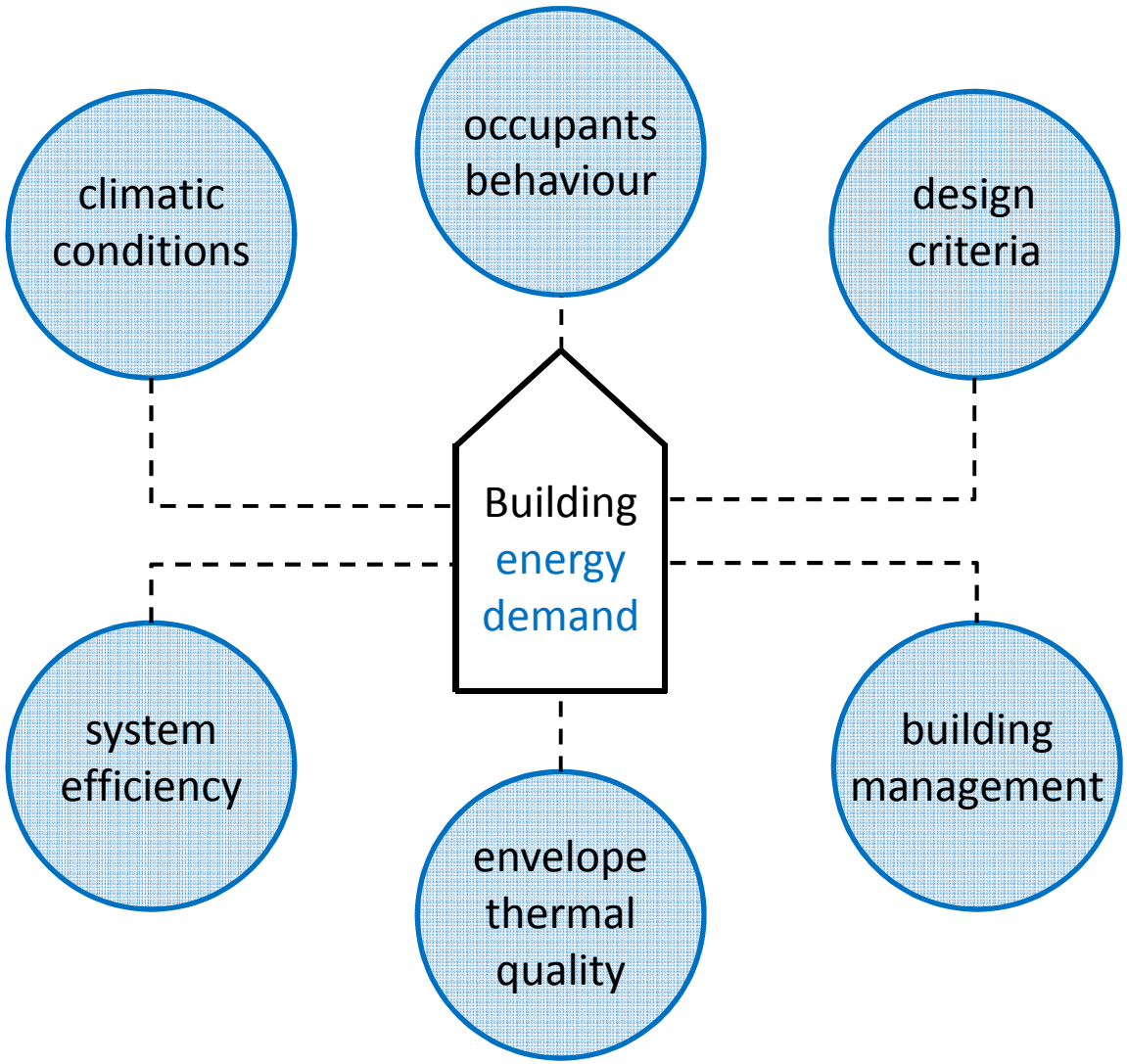
directive 2012/27/EU → Public buildings

- Buildings refurbishment
- Energy audit
- Energy monitoring
- Energy efficiency plans
- -20% primary energy

starting from 2014 there is the obligation to refurbish at least 3% per year of the total surface of public buildings

medium and long-term interventions and operational strategies in order to improve buildings energy efficiency, identifying the cost-optimal ones

in order to identify the actions needed to enhance buildings energy performance and the control strategies, it is important at a first step to define a method of energy analysis and diagnostics



case by case energy diagnosis of a large stock of buildings is onerous :

- extensive monitoring campaigns
- field surveys
- energy performance calculation

How to perform an energy audit of a large stock of buildings ?

objective

starting from a large stock of buildings, grouping them based on their similar features and find a reference building for each cluster

method

1. energy signatures
2. multiple regression model
3. cluster analysis and validation

case study

42 high school buildings

north- east of Italy





1. ENERGY SIGNATURES

ANNEX B of EN 15603:2008
Energy Signatures

A simplified method, suitable for large stock of buildings:

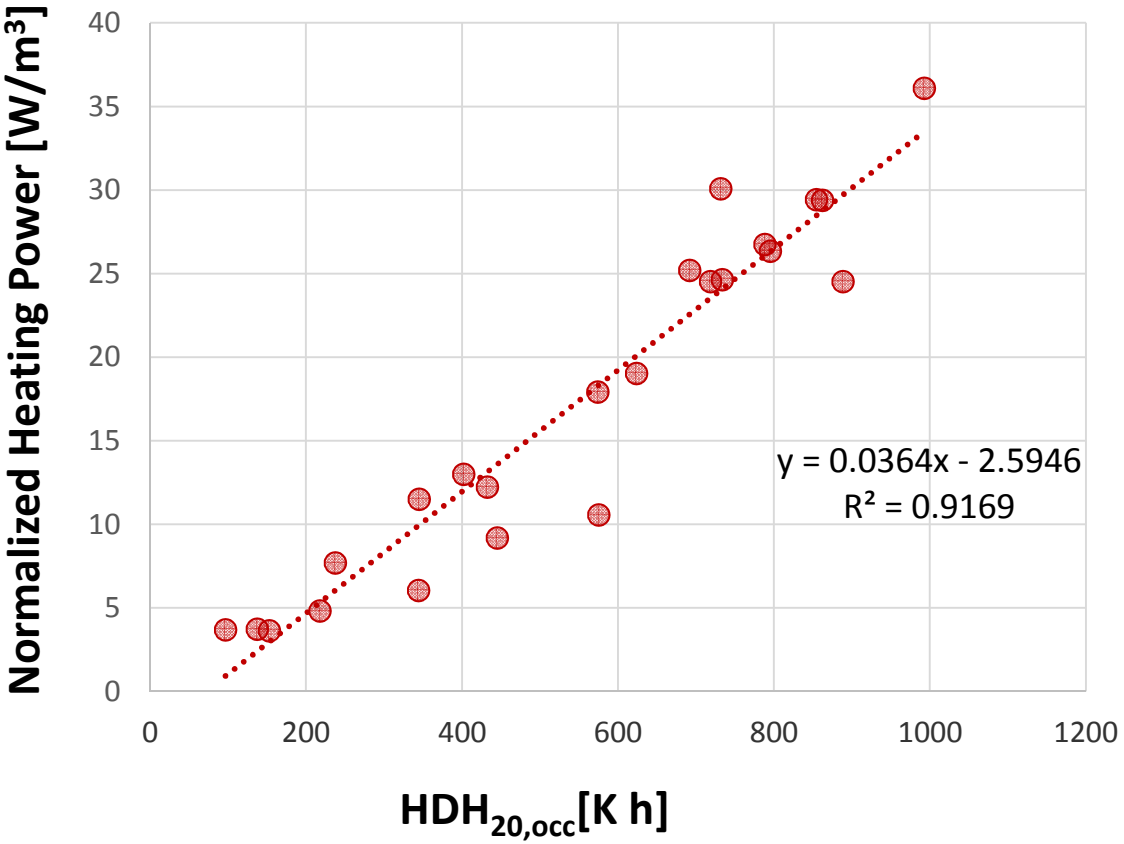
heating and cooling energy demands of a given building are correlated to climatic data over a suitable period

preferably applied for buildings with stable internal gains and relatively low passive solar gains

useful information on building energy performance and allows :

- fast detection of malfunctions or changes in the building operation/features
- the verification of the efficacy of any retrofit interventions

Energy Signature



Normalized Heating Power [W/m3]

the average weekly power per unit volume, obtained by dividing the energy use during one week per unit volume by the amount of opening hours per week

$$\phi = \sum_{i=1}^{7} \frac{EP_{h_i}/V}{\tau}$$

$HDH_{20,occ}$[K h]

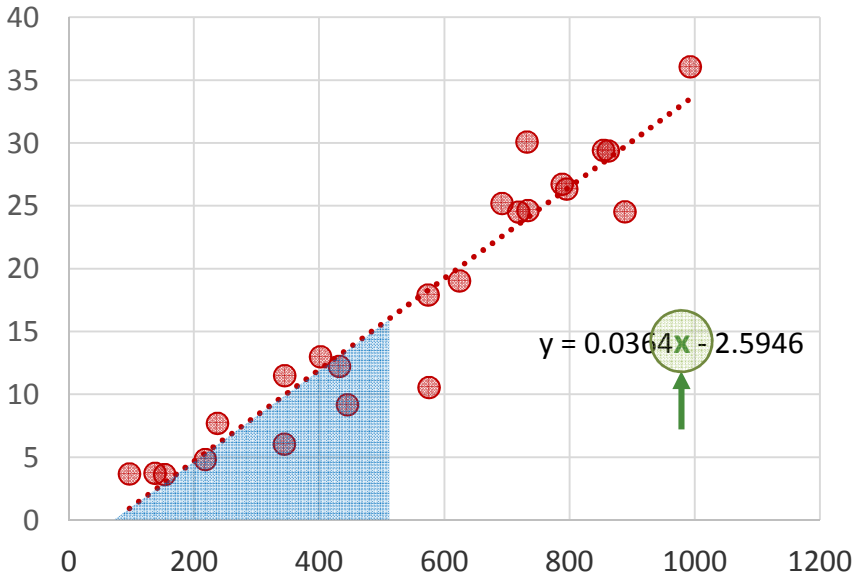
the weekly heating degree-hours during the opening hours

$$HDH_{20,occ} = \sum_{i=1}^{n} (20 - T_{ext})_i$$

n = opening hours of a week

2. MULTIPLE REGRESSION MODEL

Energy signature



zero of the function

represents the minimum number of $HDH_{20,occ}$ for which the system has to be turned on:
the higher is the intercept, the better is the passive building thermal performance

slope

represents the energy performance of the building:
the steeper the slope, the larger is the heating power needed

dependent variables

correlation with some building parameters

12 descriptive parameters

DESIGN CRITERIA

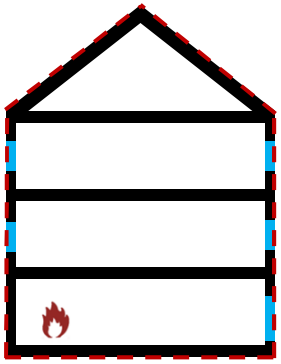
- roof area
- ground floor area
- floor area
- vertical walls area
- windows to walls ratio
- windows to floor ratio
- compactness ratio S/V

ENVELOPE CHARACTERISTICS

- transparent envelope
- opaque envelope area
- transparent to opaque envelope ratio
- average envelope U value

HEATING SYSTEM

- heating system capacity



normalized using the highest value in the whole dataset

multiple linear regression :

find the sets of the candidate quantities which better define homogenous groups

best number of predictors which allow the highest R^2_{adj}

top 10 combinations

clustering

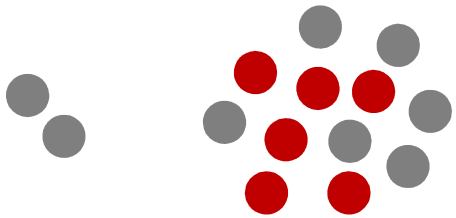
statistical significance?
R^2_{adj}
F-tests
p-values

1 dipendent variables
zero of the funcion
slope

12 predictors

2 predictors

12 predictors

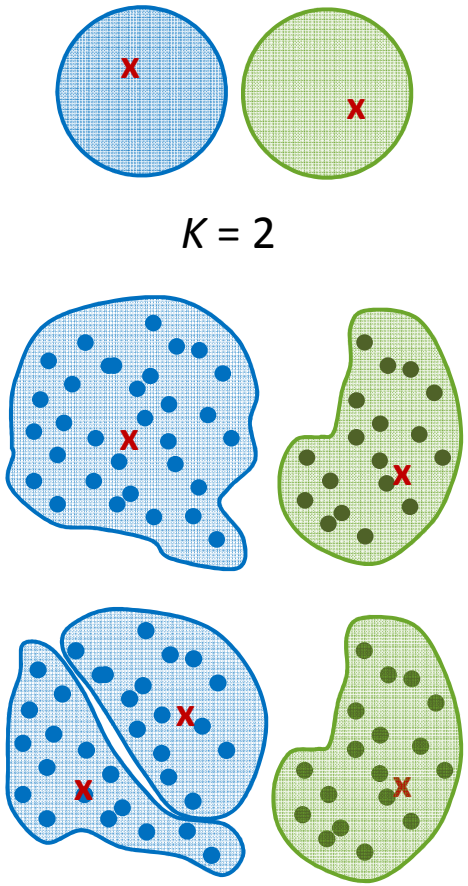


best ID configurations

3. CLUSTER ANALYSIS AND VALIDATION

the *K*-means approach :

a simple partitional algorithm that tries to find *K* non-overlapping clusters



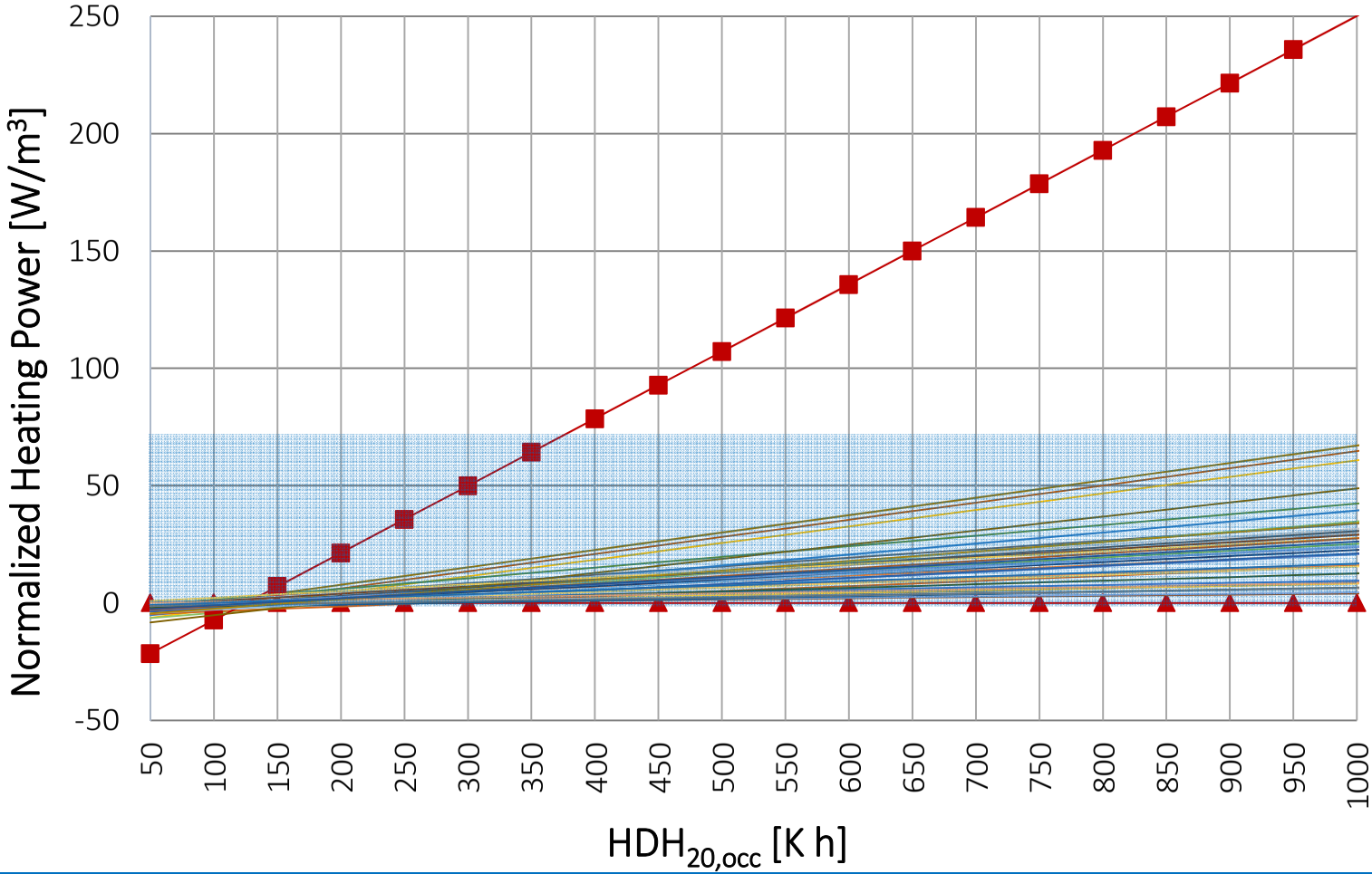
K = 2

- definition of the desired number of clusters
- randomly identification of the virtual centroids
- data points (schools) distribution according to calculation of the distance to the closest centroid
- checking if the combination of predictors with the highest R^2_{adj} previously chosen with respect to the whole dataset is the best for the cluster as well

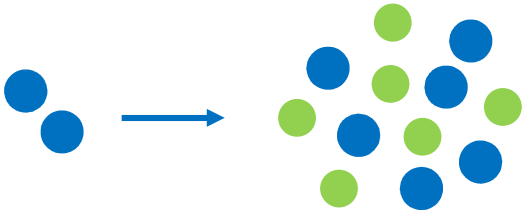
if not ✗

- the combination of predictors with the highest R^2_{adj} is found with another regression and used as new coordinate system, considering to split the clusters

1. ENERGY SIGNATURES



2. MULTIPLE REGRESSION MODEL



6 predictors → highest R^2_{adj}

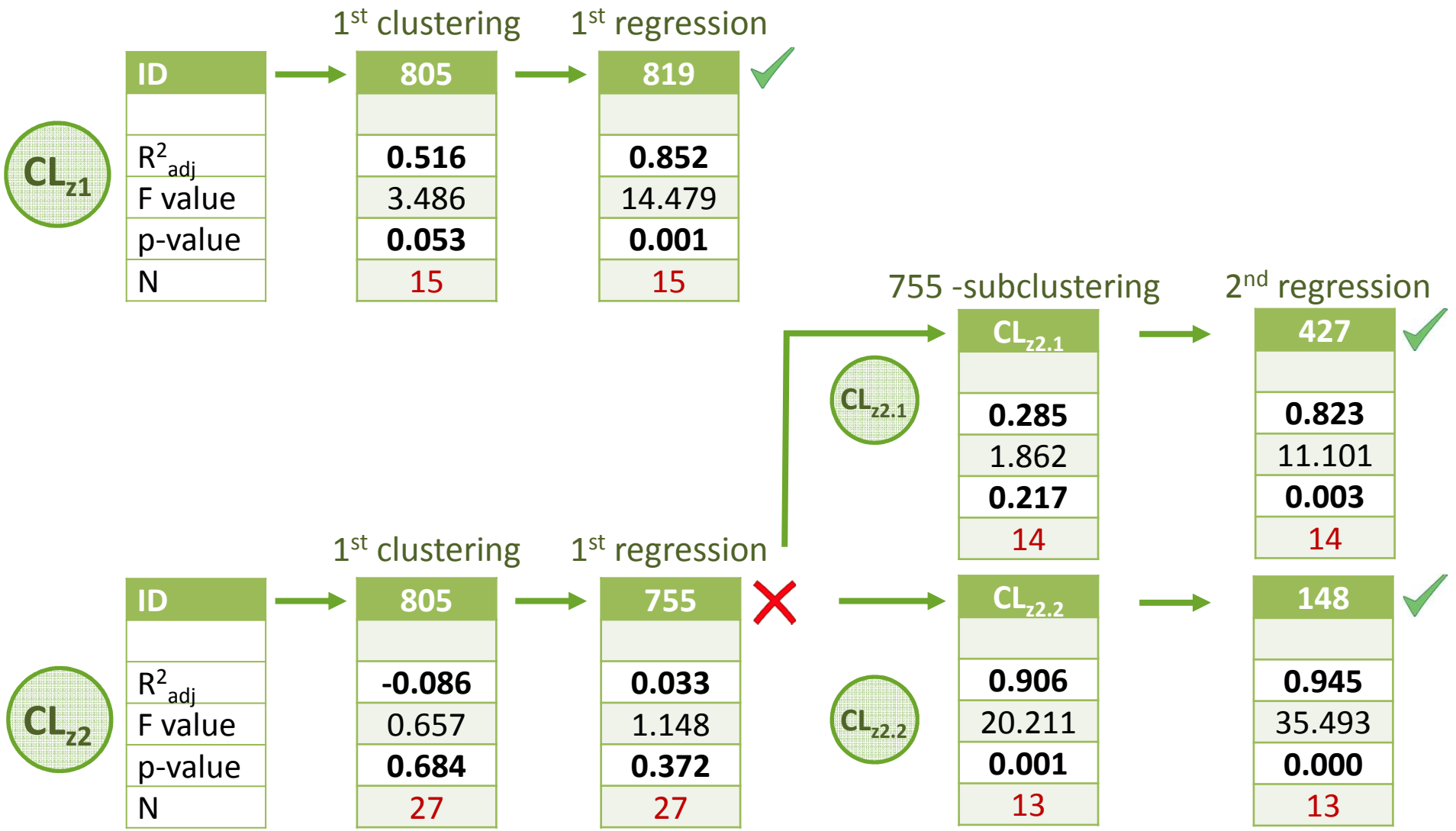
924 combinations → top 10 configurations

Zero of the function										
ID	**805**	**286**	**861**	**346**	**356**	**614**	**871**	**851**	**872**	**362**
R^2_{adj}	0.16	0.15	0.15	0.15	0.15	0.14	0.14	0.14	0.14	0.14
F value	2.27	2.24	2.23	2.17	2.16	2.16	2.15	2.15	2.11	2.11
p-value	0.06	0.06	0.06	0.07	0.07	0.07	0.07	0.07	0.08	0.08

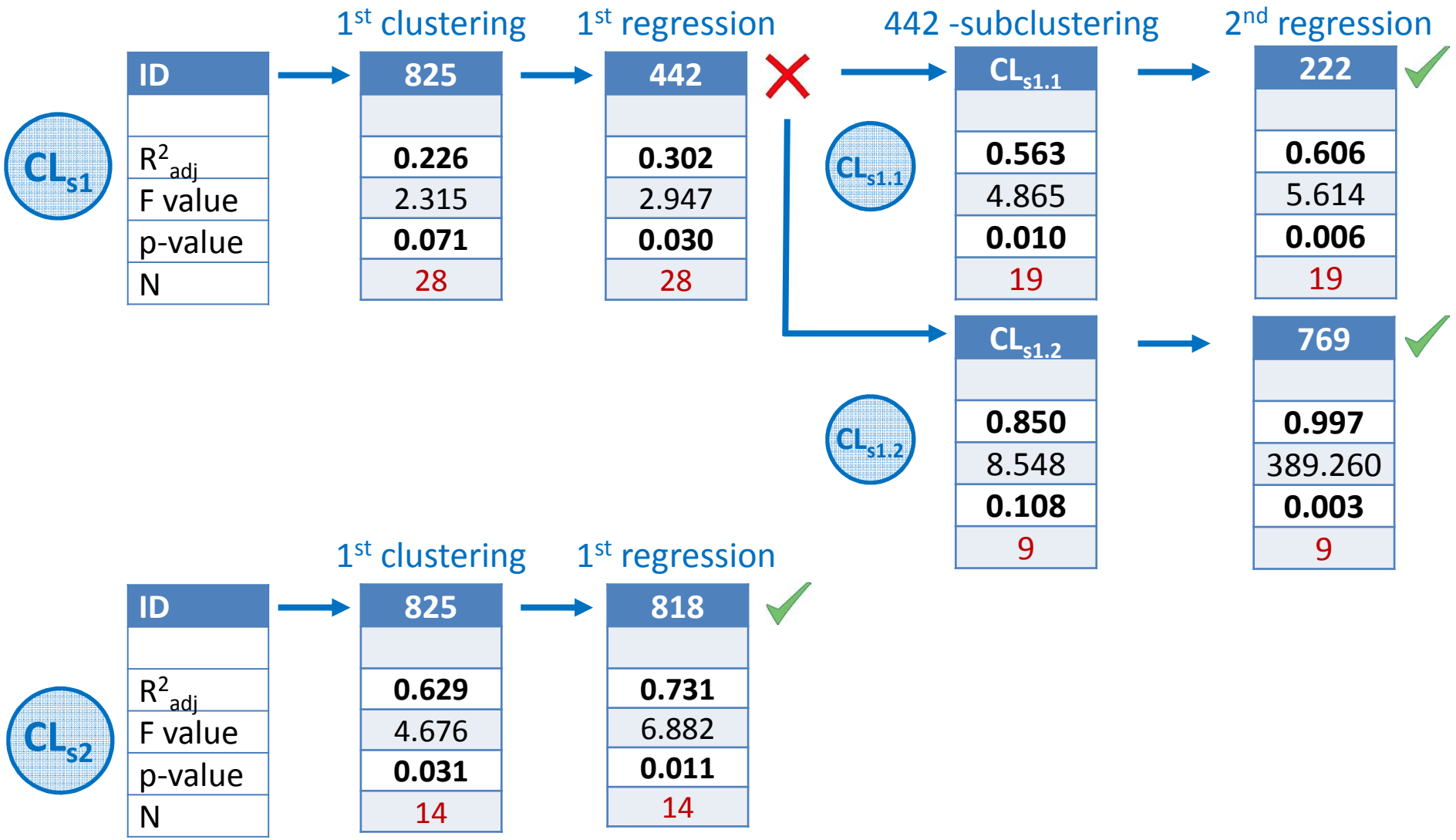
Slope										
ID	**902**	**557**	**662**	**761**	**661**	**822**	**627**	**881**	**825**	**762**
R^2_{adj}	0.17	0.16	0.16	0.15	0.15	0.15	0.15	0.15	0.15	0.15
F value	2.38	2.34	2.28	2.23	2.22	2.21	2.20	2.20	2.19	2.18
p-value	0.05	0.05	0.06	0.06	0.06	0.07	0.07	0.07	0.07	0.07

3. CLUSTER ANALYSIS AND VALIDATION

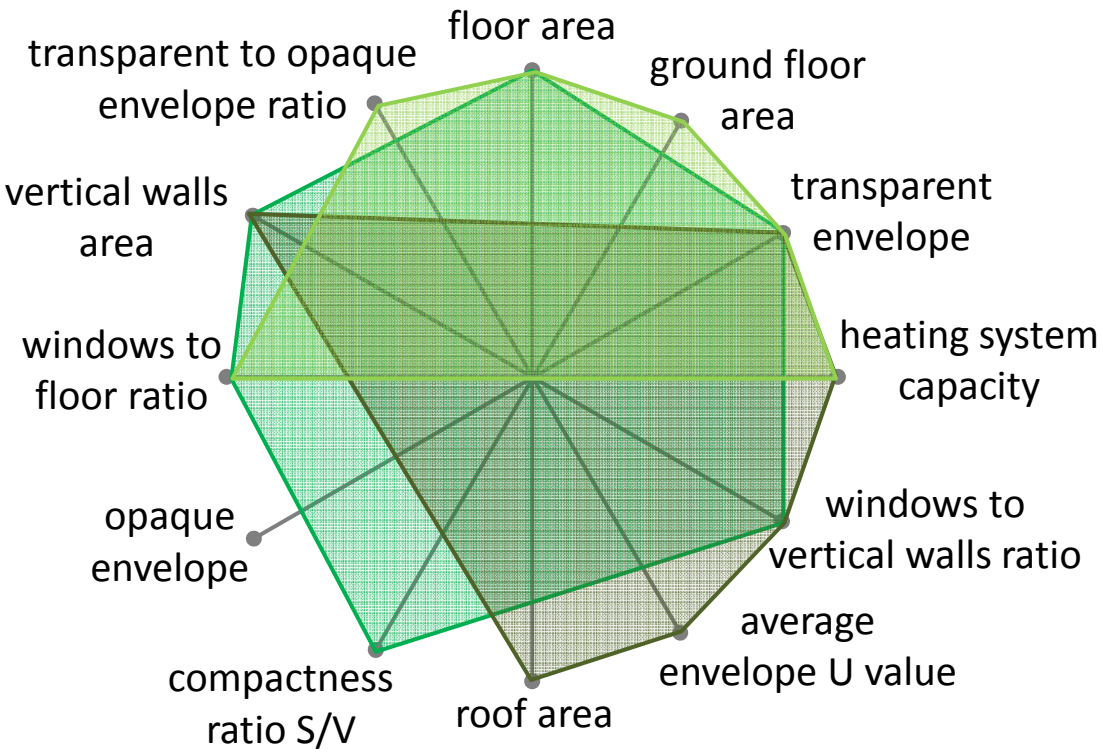
		Zero of the function									
ID		**805**	**286**	**861**	**346**	**356**	**614**	**871**	**851**	**872**	**362**
CL_{z1}	R^2_{adj}	**0.516**	0.322	0.121	0.558	0.100	0.225	-0.282	-0.011	-0.006	0.004
	F value	3.486	1.870	1.734	3.107	1.558	1.339	0.707	0.941	0.966	1.020
	p-value	**0.053**	0.254	0.153	0.146	0.203	0.579	0.686	0.483	0.466	0.434
	N	**15**	12	33	11	31	8	9	34	34	34
CL_{z2}	R^2_{adj}	**-0.086**	0.102	0.325	0.066	0.286	0.006	0.012	0.597	0.836	0.255
	F value	0.657	1.550	1.641	1.355	1.666	1.034	1.067	2.730	6.937	1.399
	p-value	**0.684**	0.207	0.426	0.273	0.323	0.425	0.407	0.433	0.283	0.570
	N	**27**	30	9	31	11	34	33	8	8	8


1st clustering
1st regression
ID
805
819
CLz1
R2adj
F value
p-value
N
0.516
3.486
0.053
15
0.852
14.479
0.001
15
755 -subclustering
2nd regression
CLz2.1
427
0.285
1.862
0.217
14
0.823
11.101
0.003
14
1st clustering
1st regression
ID
805
755
CLz2
R2adj
F value
p-value
N
-0.086
0.657
0.684
27
0.033
1.148
0.372
27
CLz2.2
148
0.906
20.211
0.001
13
0.945
35.493
0.000
13

		Slope									
ID		**902**	**557**	**662**	**761**	**661**	**822**	**627**	**881**	**825**	**762**
CL_{s1}	R^2_{adj}	0.109	0.200	0.091	0.249	1.00	0.020	0.117	0.141	**0.226**	0.522
	F value	1.388	1.960	1.469	2.772	-	1.078	1.732	1.929	2.315	2.640
	p-value	0.290	0.129	0.234	0.032	-	0.413	0.152	0.111	**0.071**	0.228
	N	20	24	29	33	1	24	34	35	**28**	10
CL_{s2}	R^2_{adj}	0.489	0.566	-0.060	0.896	0.148	0.014	0.763	-	**0.629**	0.149
	F value	4.349	4.701	0.886	12.484	2.155	1.040	4.753	-	4.676	1.906
	p-value	0.010	0.013	0.556	0.076	0.072	0.450	0.337	-	**0.031**	0.119
	N	22	18	13	9	41	18	8	7	**14**	32


1st clustering
1st regression
442 -subclustering
2nd regression
CLs1
ID
R2adj
F value
p-value
N
825
0.226
2.315
0.071
28
442
0.302
2.947
0.030
28
CLs1.1
0.563
4.865
0.010
19
222
0.606
5.614
0.006
19
CLs1.2
0.850
8.548
0.108
9
769
0.997
389.260
0.003
9
1st clustering
1st regression
CLs2
ID
R2adj
F value
p-value
N
825
0.629
4.676
0.031
14
818
0.731
6.882
0.011
14

involved predictors: zero of the function



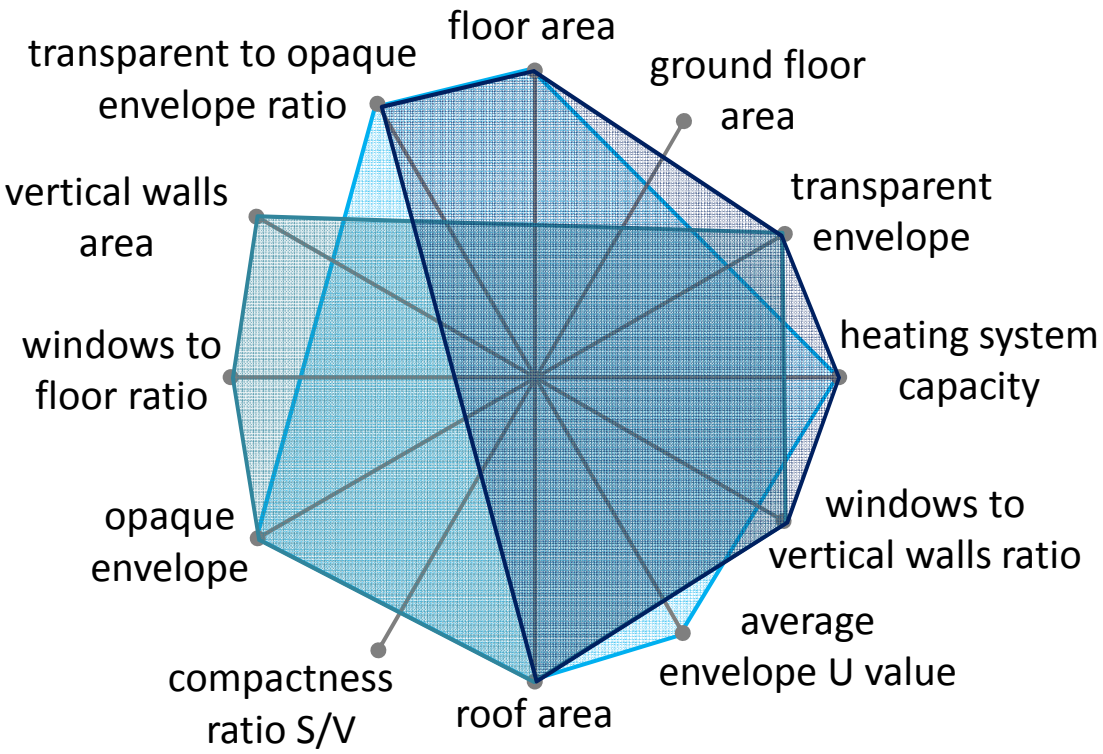
schools identified as cluster centroids

CL_{z1} : CN042_01

$CL_{z2.1}$: TV032_01

$CL_{z2.2}$: VV127_01

involved predictors: slope



schools identified as cluster centroids

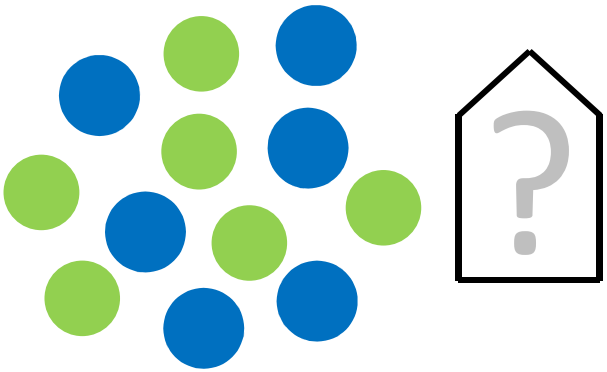
CL_{s2} : TV116_01

$CL_{s1.1}$: MB083_02

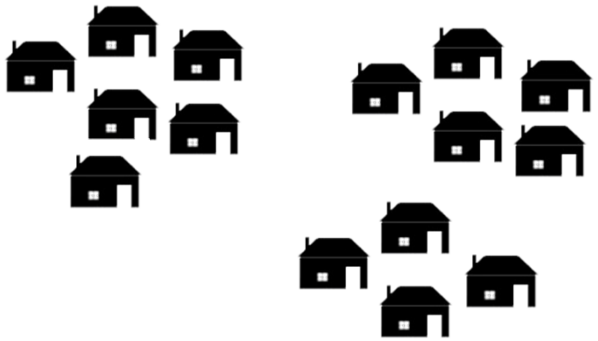
$CL_{s1.2}$: CN042_01

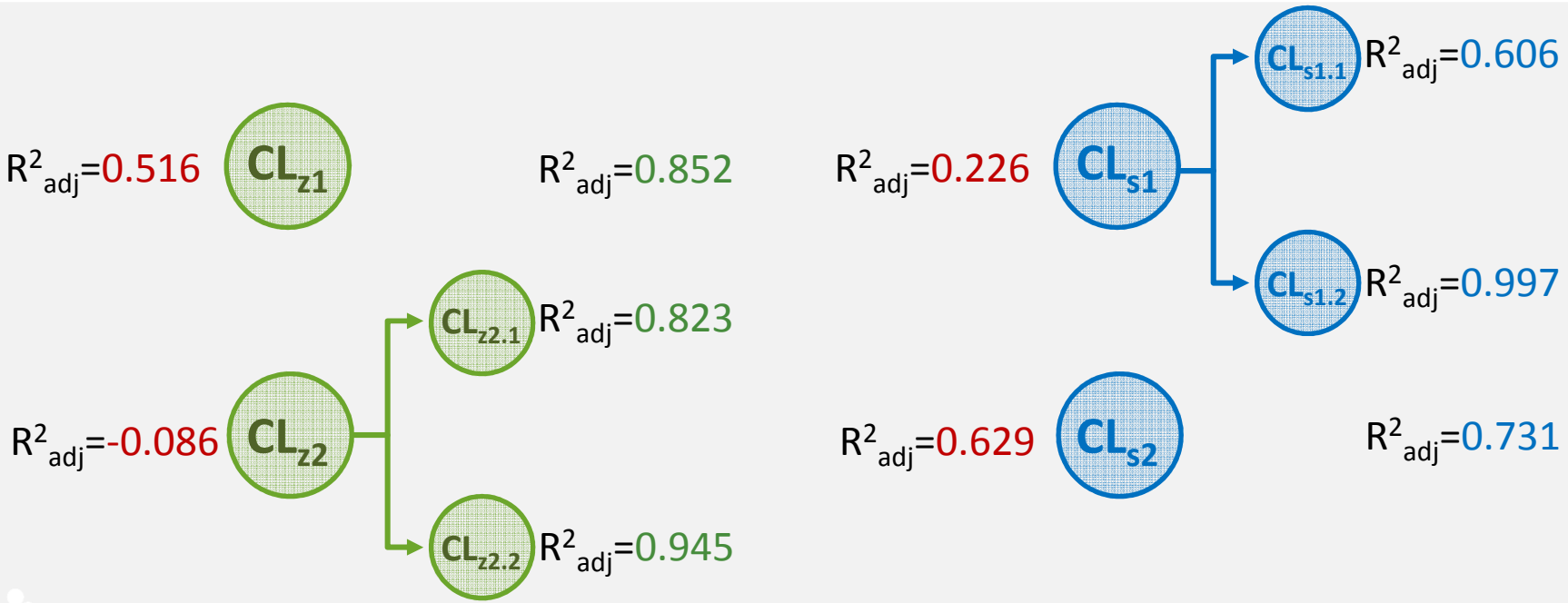
- Starting from few data about a large building stock, using the energy signature method it has been possible to analyze and compare buildings energy performance without onerous and long-term monitoring campaigns

- Starting from 12 descriptive variables, correlated with the normalized zero of the functions and the normalized slopes of the outcome energy signatures, it has been possible to highlight 6 most influencing predictors



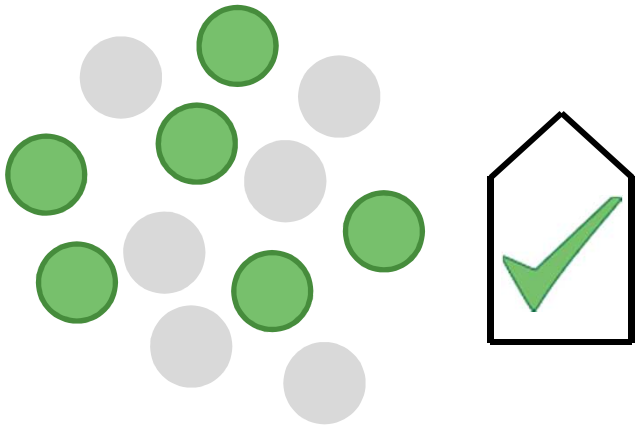
- After the identification of the best group of predictors, a cluster analysis has been performed and validated
- Data in the clusters have been studied and optimized with regressions, obtaining a good improvement in the R^2 values





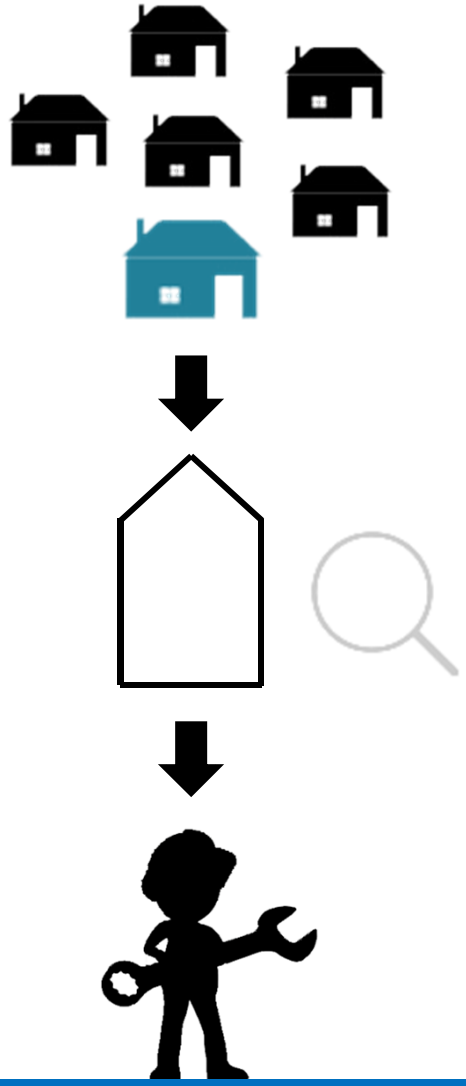
- For each cluster, the reference building has been identified

- For each final best ID configuration, it has been possible to select the 6 predictors that describe the set of school included in the clusters, which can be, in additional phase, the areas of intervention to act on



- Taking into account the set of variables most influencing each cluster of schools, it will be possible, using a cost-optimal approach, to list the potential interventions, starting from the reference building and extend these solutions to the other schools in the same cluster

- Conducting the *ES approach* also in the further years, there is the possibility to check the potentialities of this method to highlight the effects of performed energy efficiency measures



THANKS FOR YOUR ATTENTION!

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